

Multispectral Machine Vision for Improved Undercarriage Inspection of Railroad Rolling Stock

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Summary: Multispectral machine vision systems have the potential to provide mechanical inspection personnel with a tool to automatically assess and monitor the condition of rolling stock. By incorporating the visible and infrared spectra with machine vision algorithms, such a system can analyze physical and thermal condition. If a machine vision algorithm determines that a component is outside its normal operating range, the other spectrum can be analyzed to determine if there is any correlated anomaly. We present preliminary results on a project developing multispectral machine vision technology for inspection of the undercarriage of rolling stock. We have developed a system to record digital video images from a below-track perspective, and several machine vision algorithms to identify and analyze features of interest in these images.

Index Terms: automated mechanical equipment inspection, machine vision, infrared, condition monitoring, safety, electrical, component

1. INTRODUCTION

Current practices for inspection of railroad rolling stock include both visual and automated systems [1, 2]. However, inspection of the undercarriage is almost entirely a manual process. Visual inspections by humans are performed either in a pit or trackside. The equipment is usually stopped over the pit or run slowly past the trackside inspector. In the latter case, it is not possible for a human to have an unobstructed view of the undercarriage as a train rolls by.

Automated inspection by electronic systems has the potential to overcome certain limitations of human inspection. The systems can be placed closer to the track or between the rails where it may be considered unsafe for a human to be positioned when a train passes. Machine vision systems have the ability to store and retrieve images and make objective comparisons of different images. Although current wayside defect detectors measure thermal energy in the infrared spectrum, they do not record images. Inspection of some components would be

enhanced if visible and infrared imagery could be stored and analyzed together.

We are developing a machine vision system to improve both the efficiency and effectiveness of this inspection process by incorporating visible and infrared range information. Critical inspection tasks that will be investigated include disc brake performance and condition, bearing component wear, incipient failure of electrical systems, and identification of missing equipment. In addition, experiments to detect foreign objects underneath the rail vehicle are planned.

2. METHODOLOGY

We evaluated the methods and configurations necessary for a machine vision system to inspect the undercarriage of railroad rolling stock. Camera location was the first to be considered because it affects various other design elements and constraints. The wheels, trucks, and any low-hanging part of the railcar would obstruct a camera view from the field side of the track. The

least obstructed view of the undercarriage is from between the rails below railhead height.

Multispectral image acquisition is required to capture the necessary data to fulfill the project requirements. A camera in the visible range is used to inspect components in the same light spectrum that humans can see. A camera in the infrared range is used to inspect the thermal condition of components and complements the visible range information. Heat energy may be created by either mechanical or electrical systems, for example, brakes and traction motors, respectively. Thermal energy is present in all components to some degree, but elevated levels may indicate overheating and possible incipient failure. Conversely, lack of thermal energy where it is expected can also indicate a malfunction, e.g. cold wheels or brake shoes during or following an application of brakes.

The system we are developing will record a train rolling overhead in both the visible and infrared spectra. With reference to stored information about components on a railcar, the system can first identify and then analyze those components for discrepancies that would indicate a failing or failed state. Since the system has both visible and infrared imaging capabilities, an anomaly in one spectrum can be correlated with the other spectrum using machine vision algorithms. Components can be analyzed against reference data, historic data, or other similar components on the car or in the train. For example, under appropriate circumstances, a stuck brake (either applied or released) will have a different thermal indication than others in the train.

With the ability for information storage and retrieval, the system also has the capability to determine trends among different pieces of equipment. For example, a brake pad that is increasingly hotter than others at consecutive inspection stations could be demonstrating evidence of component wear. Detected defects or incipient failures can trigger alerts and also be stored in memory for future reference by inspectors or the machine vision system itself.

3. MACHINE VISION SYSTEM

The machine vision system consists of the image acquisition system and computer algorithms for interpretation of rolling stock components in the camera's view. Design of the machine vision system for undercarriage inspection is determined by the following factors: 1) the characteristics of a video acquisition system and environment in which the video of a moving rail vehicle is

recorded, 2) the geometric and photometric properties of undercarriage components appearing in the video, and 3) the accuracy, generalizability and real-time requirements of the inspection system.

3.1 Image Acquisition System

In machine vision installations for rolling stock inspection, the camera is generally stationary while the vehicle rolls past [2, 3, 4]. Obtaining video images of the undercarriage of rolling stock imposes additional restrictions on the recording equipment not encountered in wayside machine vision systems. Initial recordings have been taken from rolling stock inspection pits. The camera is located below rail level and looks upward at the bottom of the vehicle (Figure 1). For the camera to see the entire undercarriage from side to side, the limiting factor for the camera's line of sight is the gauge face of the rail. This creates an inverted triangle in which two corners are formed by the bottom-outside edges of the railcar and the third by the camera. Based on previous experience [2, 3, 4], we decided that the best orientation of the camera was perpendicular to the undercarriage of the rolling stock.

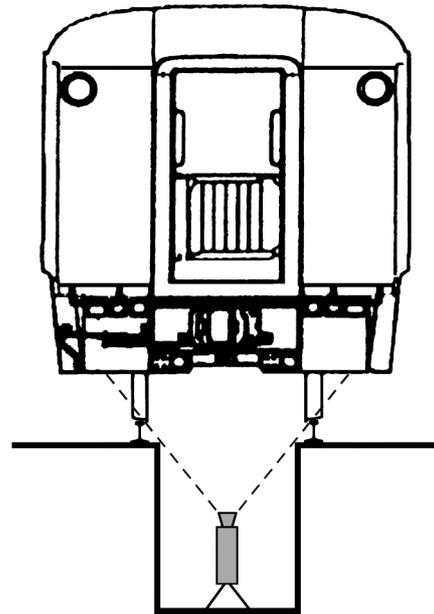


Figure 1: Camera Perspective From Beneath Railcar

3.1.1 Visible Spectrum Recordings

A digital video camera was selected that records images with a 640x480 pixel resolution. The camera is mounted inside a weatherproof enclosure to protect the camera from the effects of weather and other environmental conditions such as dripping fluids, dust, dirt, and any other

material from the undercarriage of the train (Figure 2).



Figure 2: Camera and Lighting Configuration Used for Preliminary Testing

The video camera is controlled by a laptop computer via a FireWire cable connection that is long enough to allow the computer to be located outside the pit. The computer is powered by standard 110 VAC and contains software that allows the user to record and store digital video images as well as adjust the shutter speed, white balance, and frame rate, etc. of the camera. The video camera records at 30 frames per second. The lens aperture is fully opened to allow for maximum light to reach the camera's charge coupled device (CCD). The shutter speed is adjusted relative to the strength of the light source in the pit. A greater amount of light enables use of a faster shutter speed and thus reduces blurring from the motion of the train.

Given the constraints on camera location, we needed to determine the focal properties needed to provide the necessary field of view in terms of image width and height. From the inverted triangle described above, we can determine a maximum depth of the camera lens below the railhead for a given piece of rolling stock. For a railcar with a maximum width of 3.2 meters (10.5 feet), 127 cm (50 inches) above the railhead, the maximum depth (l) is calculated using Equation 1.

$$\frac{127 + l}{320} = \frac{l}{143.5}$$

$$l = \frac{18244.5}{176.5} = 103.25\text{cm} \quad (1)$$

The video camera has two characteristics that determine the field of view: the CCD size and the

focal length of the lens. Our current camera has a 13mm ($\frac{1}{2}$ inch) CCD. Equation 2 is a general equation that relates focal length (f) with distance from scene to lens (D) and horizontal width (w). Given that the horizontal width is 1,435 mm (4 feet 8.5 inches) at railhead height, a maximum distance of 103.25 cm (40.65 inches), and the constant (k) of 6.4 for a 13mm ($\frac{1}{2}$ inch) CCD [5], the maximum focal length yields,

$$f = k \frac{D}{w} = 6.4 \frac{1032.5}{1435} = 4.6\text{mm}. \quad (2)$$

We determined that a lens with a 3.6-mm focal length yielded images that were satisfactory for our testing (Figure 3). This is one millimeter shorter than the maximum focal length, to accommodate a camera enclosure over 30.5 cm (12 inches) in length mounted on a tripod used in pits as shallow as 1.2 m (4 feet).

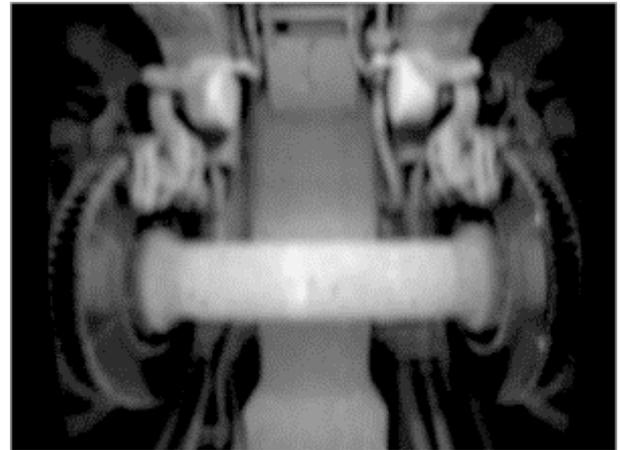


Figure 3: Visible Spectrum Image of Axle and Disc Brakes

Changing the focal length of the camera is a balance between several factors. Increasing the focal length to its calculated maximum reduces the fish-eye effects of the lens and therefore produces better quality at the edges of the image. However, a larger focal length also increases the distance from scene to lens necessary to obtain the requisite width and therefore requires positioning the camera farther below the railhead. Conversely, shorter focal lengths reduce the depth of the camera installation, but cause greater warping of the image.

3.1.2 Infrared Spectrum Recordings

Similar considerations are needed for infrared imaging. Current infrared cameras do not offer focal lengths as short as visible range cameras. If the camera cannot capture the entire width of the undercarriage, it can be positioned to capture a select section (Figure 4). Multiple cameras can

then be employed to capture the remainder of the undercarriage as necessary.

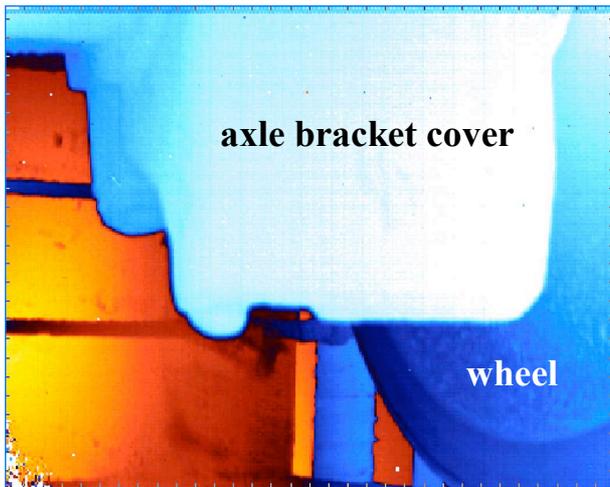


Figure 4: Infrared Image of Locomotive Wheel

3.1.3 Image Quality from Recordings

When working with two different energy spectra, certain recording requirements are shared between both systems, while others are spectrum specific. Both imaging systems require high frame rates and fast shutter speeds to capture clear, detailed images. Ambient light levels will generally be inadequate to obtain sufficient sharpness in visible spectrum images of undercarriage components; therefore, artificial lighting is required to produce the necessary illumination. Testing revealed that the light sources must be sufficiently diffuse to prevent multiple shadows on the undercarriage. A comparison of an image recorded in our first test (Figure 3) and one recorded in a subsequent test (Figure 5), in which light level and balance were enhanced, demonstrates the resultant improvement in image clarity.



Figure 5: Wheelset with Improved Illumination

By contrast, because the infrared camera measures the heat energy, or emissivity, of the source itself, it needs no external source of lighting. Since the cameras are in exclusive energy spectra, the artificial lighting source has no discernable effect on the ability of the nearby infrared camera to pick up the emissivity of the undercarriage of the railcar.

3.2 Machine Vision Algorithms

The goal of machine vision algorithms for undercarriage inspection is to detect and segment components, to discover missing or damaged objects, and to detect the presence of incipient failures. Therefore, another set of important factors in considering machine vision algorithms is the appearance of the components of interest in the video. The selection of the appropriate algorithms also depends on the quality of lighting, resolution, and other imaging conditions as described above. We have studied several image-analysis approaches in order to select the set with the best performance in undercarriage inspection.

The measurement criteria of the system's performance must be developed to reliably accomplish the inspection tasks such as detecting variations from the norm in appearance, shape, and/or temperature of components. The normal values for these parameters and their allowable variations can be learned from a set of training images and from other similar components in the car or train. If the detected variation exceeds the specifications, the system could automatically set off an alert about the defect. This alarm can be sent as a report for the railroad inspection system, including how certain the machine vision algorithm is that the defect is present. Images in the visible and infrared range can be sent to inspection personnel to further analyze the defect.

We are also interested in algorithms that are amenable to inspection of a wide range of undercarriage components. Rather than implement a different set of algorithms for each component, our approach is to develop solutions that are sufficiently general that a wider range of equipment types and their components can be addressed within a unified framework. This will also allow faster processing times, another important factor in design choices.

3.2.1 Panoramic Image Creation

A panoramic image of an individual railroad vehicle is created to allow the system to perform a matching algorithm to determine the type as

well as pick out individual components. Panoramic images are created for both the visible and thermal ranges in order to correlate them to each other. Panoramic ‘stitching’ is useful when a component is larger than the field of view for a camera (Figure 6).

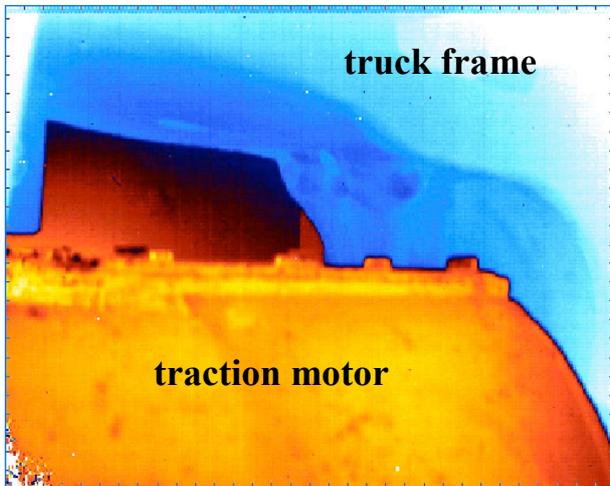


Figure 6: Infrared Image of Traction Motor Edge

When the camera is oriented perpendicular to the object it is recording, the panoramic process takes two individual steps to complete: image dewarping and image stitching. The lens used to capture video creates a fish-eye effect on each individual frame. The images are first dewarped, based on knowledge of the lens distortion, to create a flat image of the picture. Then, to minimize loss of detail, a thin strip from the center of each image is saved. The strips from consecutive images are then stitched together to create a single, panoramic image.

The panoramic image creation varies if multiple cameras are used in recording the undercarriage in one spectrum. In the case of multiple images at discrete angles, the images are first dewarped from lens distortion. Before being stitched together, any image from a camera not perpendicular to the captured object needs to be rotated to a flat orientation through a homographic transform. Selected areas of the transformed image are then stitched side-by-side and end-to-end to create the panoramic view.

3.2.2 Component Detection Algorithms

When designing an algorithm for detection and segmentation of components, we are primarily concerned with the accuracy, generalizability and real-time requirements of the railroad inspection system. For accuracy, the detection rate of true defects should be sufficiently high and the false alarm rate sufficiently low. For generalizability,

the algorithms developed for inspection of one undercarriage part should be easily modified for inspection of other parts, and if possible, the algorithmic solutions should be able to handle more than one type of a car. Finally, for real-time requirements, algorithms must have the appropriate balance between speed and quality to be useful to inspection personnel. There are many sophisticated machine vision systems that are not appropriate for this purpose. Although some may produce very accurate detection and segmentation results, which lead to accurate car undercarriage inspection, their performance is accomplished at the expense of long processing time.

We selected traction motors as one of the initial components to test component identification. Traction motors appear as a rectangular-shaped object, positioned along the locomotive’s longitudinal axis. Due to the camera position beneath the train, it is possible to select optimal frames from the video that contain the frontal view of the target component. Thus, the first step of our algorithm for detection and segmentation of traction motors is to select the optimal frame, such that the traction motor is positioned closest to the image center (Figure 7). Consequently, it is necessary to detect where the traction motor appears in the sequence of frames.



Figure 7: Original Image of Traction Motor

The traction motor appears in the image as a rectangular homogeneous region. To identify the traction motor, it suffices to first detect edges in the image by using an edge detector. Edge detection is a well-studied problem in machine vision, for which there are numerous off-the-shelf algorithms. We use the Canny detector, which views edges in the image as abrupt changes in gray-level intensity, and hence searches for maxima in the gradient of the image (Figure 8). Concentration of lighting on component parts

creates glare that makes it difficult for the algorithm to detect edges. Also, components that are closer to the camera appear to move faster than those farther from the camera, which can cause motion blurring of edges in the image.

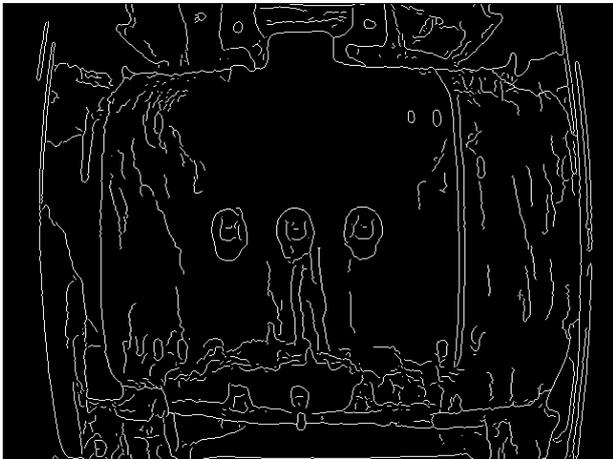


Figure 8: Edge Detection of Traction Motor

As a result, edge detection produces curve fragments instead of fully connected boundaries of objects in the image. Therefore, we have to implement an algorithm that completes disconnected curve fragments, and thus segments the traction motor. Since the traction motor appears as a large homogeneous region containing three characteristic circular subparts (i.e., bolts), we first localize such a region in the image. Homogeneity here is measured with respect to gray-level intensity of pixels within a region. Then, only those curves that enclose the identified homogeneous regions are connected (Figure 9).

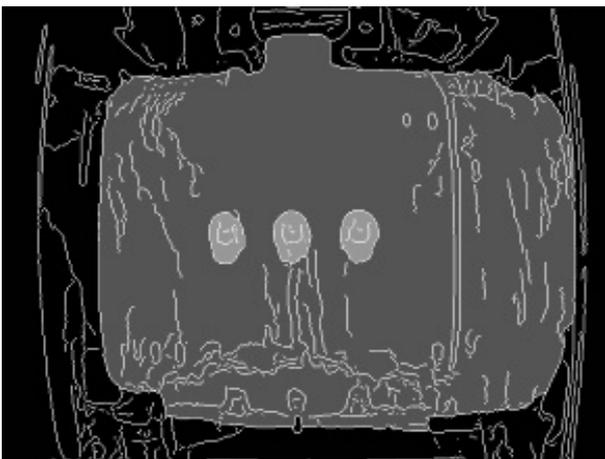


Figure 9: Segmentation of Traction Motor

Finally, from a video sequence of images in which we detected and segmented the traction motor, we select the one where the horizontal axis of the traction motor is the closest to the

image center. The selected image is called the optimal frame, since it is assumed that the explained detection and segmentation is the most accurate for that image.

The traction motor was chosen as one of the first components to be detected for several reasons related to the project objectives: 1) railroad industry advisors to the project expressed particular interest in this capability, 2) generalizing this algorithm would allow detection of traction motors on different types of locomotives, and 3), traction motors are a source of thermal energy and thus provide an opportunity to correlate the detected warm areas with the visible spectrum images. A segmentation algorithm was also developed for disc brakes and axles (Figure 10) for similar purposes.

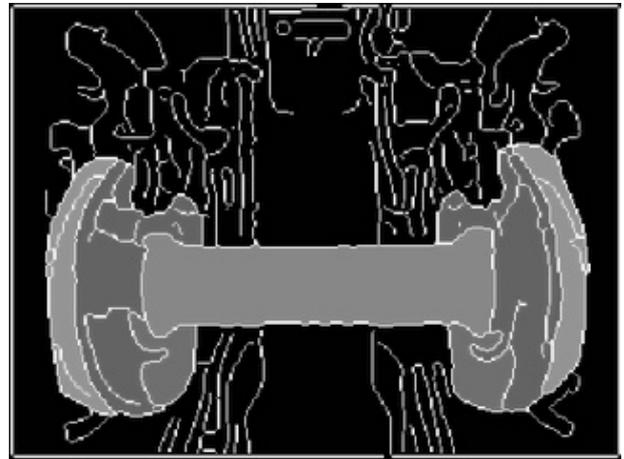


Figure 10: Segmentation of Disc Brakes and Axle

3.3 Registration of Visible and Thermal Images

In some cases, undercarriage component defects are not viewable in the visible light spectrum. The shape, position, and appearances do not deviate from accepted parameters, but it may be possible to detect incipient failures due to thermal irregularities detected by the infrared camera. Our goal is to capitalize on the advantages of each system by comparing the two complementary sources of information. The heat of one part is easily transmitted to another in conductive materials, like metal; therefore, edge demarcation is less well defined. Consequently, it is difficult to analyze individual infrared images alone to accurately determine which component is overheating (Figure 11).

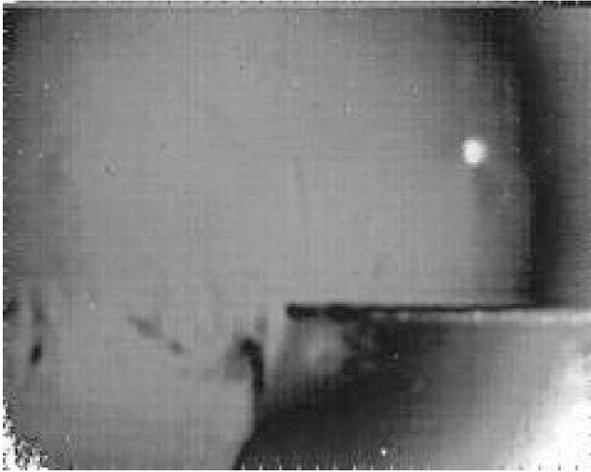


Figure 11: Infrared Image Showing Hotspot on Traction Motor

To alleviate this problem, the machine vision system can analyze both the visible spectrum and the corresponding infrared image of the undercarriage. Taking cues from the thermal image, the visual system is better able to identify the component of interest, precisely delineate its boundaries, and superimpose the detected boundaries onto the infrared image. The heated area with the highest intensity in the infrared image will be uniquely identified as a part worthy of further attention. Therefore, we will correlate the two sources of information coming from the visible and infrared cameras.

4. DISCUSSION

The system currently under development will analyze railroad rolling stock undercarriages for inspection of components in both the visible and infrared spectra. It is intended that it will provide an adaptable framework that will enable further enhancement to improve its capabilities and automation.

As a larger database of undercarriage components and rolling stock is developed, comparisons with known conditions by reference to stored information can be used to inspect the cars and train being recorded. This can be done at different levels of granularity starting from an equipment type, to a fleet, down to individual vehicles. The finer the granularity, the more precise the component and overall undercarriage monitoring becomes. If granularity is kept at a level of type or fleet, more recorded images are beneficial in creating an optimal panoramic template to compare against a car for any of that group. The system can also reference a vehicle's Automatic Equipment Identification information to automate the data retrieval and storage abilities.

4.1 Image Alterations Induced by Weather

All video recordings completed so far have been under good weather conditions without any effects of rain or snow. We are scheduling recordings under winter conditions in subsequent months. We anticipate that moisture on the undercarriage of cars will enhance the reflectivity of objects in the visible range and will have no effect on the emissivity of temperature in the infrared range.

Packed snow will provide a challenge for both the visible and infrared range. As snow builds up, we expect that the ability to detect detail on objects on the undercarriage will be diminished. Infrared cameras can only detect the heat of the nearest physical object, so the snow buildup itself will register rather than the component above it. Components that remain warm may not experience snow and ice accumulation, in which case the infrared camera should be able to detect the actual temperature.

5. CONCLUSION

From this work we hope to demonstrate that automated, multi-spectral machine vision systems can provide mechanical inspection personnel with a tool to assess and monitor the condition of rolling stock between maintenance and service visits from a below-the-track perspective. Such a system would provide enhanced analysis of components and compare them to reference data and/or similar components in the train to determine temporal and spatial trending. By incorporating the visible and infrared spectra into automated machine vision algorithms, more effective analysis is possible. The correlation of images from separate sources can enrich the inspection information of undercarriage components, improve the analysis over what each spectrum provides separately, and provide more useful information for individual vehicle record-keeping and to mechanical inspection personnel.

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